Online Appendices

A 1-Labor and Capital Investment Decisions

The model includes endogenous managerial decisions on how much capital and labor to acquire. These decisions are modeled to follow labor and capital levels that are profit maximizing given a level of demand, desired service quality, compensation, and task richness. To calculate these decisions three steps are followed:

1) Unit employee cost, unit asset cost, and unit capability costs are calculated
2) Profit maximizing budget, capital, capability, and employee levels are calculated
3) Capital, capabilities, and labor are gradually adjusted towards their profit-maximizing values

The formulations for these steps are discussed in more detail below. All formulations are documented in the full model documentation.

Step 1)

Unit employee cost per month includes the monthly compensation plus employee's cost of hiring and training spread across their expected tenure (given compensation):

$$C_E = c + (c_h + c_t)/Max(\tau_{V\_min}, \tau_{V_b}\left(\frac{c}{c_N}\right)^{\theta_c \xi})$$

c_h: Minimum hiring costs

c_t: Additional training and hiring costs which helps with finding/training better employees

Unit asset (human-independent capital) cost per month is anchored to the capability cost. It is calculated to include the cost of building one unit of capability with unit employee quality and normal capability life. This baseline cost is then adjusted with a parameter, a_A, signifying the relative cost advantage of assets. For comparability with other factors asset costs are spread over time as rents:

$$C_A = \frac{c_N}{e_C t_b a_A}$$

a_A: asset cost advantage over capabilities

Unit capability cost accounts for the cost of employees needed to build one unit of capabilities (given current employee quality) and the current capability life:

$$C_C = \frac{C_E}{e_c Q \mathrm{T}}$$

Step 2)

Using the desired service quality of s, we can find the desired service capacity, P_D:

$$P_D = s\kappa C^{\alpha\beta} A^{\alpha(1-\beta)} E^{(1-\alpha)} Q^{(1-\alpha)\beta} = sD$$

Then, taking current quality as given, we solve for the desired levels of assets A_D (and employees and capability) that minimize the costs of that capacity given the unit costs of factors of production from step 1. This results in:

$$A_D = B_D \alpha(1-\beta)/C_A$$

Where desired budget, B_D is:

$$B_D = \frac{sD}{\kappa\left(\frac{\alpha\beta}{C_C}\right)^{\alpha\beta}\left(\frac{\alpha(1-\beta)}{C_A}\right)^{\alpha(1-\beta)}\left(\frac{1-\alpha}{C_E}\right)^{(1-\alpha)} Q^{(1-\alpha)\beta}}$$

We could find the desired employee and labor similarly, from the same optimization problem. However, we note that assets typically move more slowly than employees and capabilities, so the goals for capabilities and labor could take current assets as given. We therefore define two more short-term problems, one to find desired capabilities given current levels of assets and another to find desired employee levels given the current level of both capabilities and assets[1]. We solve the analogues (but simpler) problems and find desired capability (C_D) and desired labor for customer service (E_{D_S}). These solutions are available as part of model equations. The desired labor for capability building (E_{D_C}) then accounts for both labor needed to maintain C_D and the labor to close the gap between current capability level and the desired level over the capital adjustment time (t_C):

$$E_{D\_C} = \frac{\mathrm{Max}\left(0, \frac{C_D}{\mathrm{T}} + \frac{C_D - C}{t_C}\right)}{e_c Q}$$

Total desired labor, E_D, is the sum of desired labor for capability building and desired labor for customer service.

Step 3)

Assets adjust slowly towards desired level:

$$\frac{dA}{dt} = (A_D - A)/t_C$$

Capability adjustment is achieved through employees who are allocated to capability building. Employee allocation first satisfies demand for customer service (E_{D_S}), then demand for capability building, and if any labor remains (E_X), it is allocated between the two purposes based on task richness, so with high task richness focus is on capability building and with low task richness the focus is on customer service:

$$E_S = \mathrm{Min}\left(E, E_{D_S}\right) + E_X(1-\beta)$$
$$E_C = \mathrm{Max}(E - E_S, 0)$$
$$E_X = \mathrm{Max}(0, E - E_D)$$

Finally, the gap between labor and desired labor (G) is closed over employee adjustment time (μ) through hiring (H) as well as the faster of layoffs or voluntary turnovers (U):

$$\frac{dE}{dt} = H - U$$
$$U = Max(-\frac{G}{\mu}, \frac{E}{\tau_V})$$
$$H = Max(0, U + \frac{G}{\mu})$$
$$G = E_D - E$$

A 2-Base case sensitivity to quality goal and behavioral decisions

The base case analysis changes two factors (compensation and task richness) keeping the third potential managerial lever, desired service quality, fixed. To assess the impact of different values of desired service quality we repeat the baseline analysis for s values of 0.7 and 1.3. Results are reported in Figure S 1. The impact of service quality goal on the tradeoffs across the two other dimensions is limited to changes in the value of payoff, but the shape of the payoff landscape and the existence and location of the two peaks remain very similar.

[1] In equilibrium the two approaches give identical results. They are also fairly similar dynamically, but the one we use leads to faster adjustments during transition and is behaviorally more realistic because it anchors the shorter-term factors on the current (rather than future optimal) value of factors with slower adjustment time.

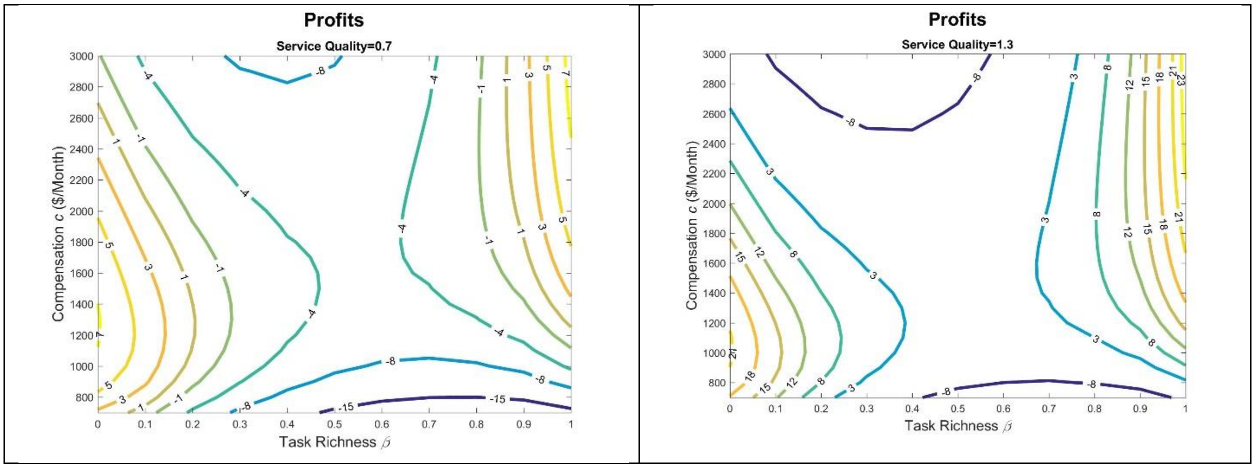


Figure S 1-Sensitivity of results to different service quality goals.

Another sensitivity analysis relates to the choice of efficient allocation functions in the model. This potentially strong assumption can be made modified to account for the anchoring of capability and service quality goals in historical values. Specifically, it may be more realistic to expect managers to anchor their current desired capability to past values and only slowly adjust towards more efficient levels. Similarly, service quality goals may be anchored to past service quality level. We assess both these possibilities by adjusting the equations for desired capability and desired service quality as follows:

$$C_D = C_D^* w_{Ceff} + C\left(1 - w_{Ceff}\right)$$

$$s = s^* w_{sExt} + \bar{S}(1 - w_{sExt})$$

Here C_D* is the efficient desired capability from the optimization problem discussed above, s* is the external desired service quality (which we had denoted as s before), $\bar{S}$ is the exponential average of actual service quality over τ_S, and w_{Ceff} and w_{sExt} are weight parameters that control the strength of behavioral information cues in desired capability and service quality decisions. Our exploration of model using these new formulations and different weights suggests the behavioral mechanisms have limited impact on the results. As long as the weights are above 0, these behavioral formulations only slow down the convergence to efficient capability and externally desired service quality, but do not otherwise change the equilibrium behavior. While not central to our theoretical analysis, the slower adjustment time is potentially relevant for assessing the exact costs of transition and profitability in response to stochastic demands, however those numerical sensitivities do not change the qualitative results. Two sample analyses are reported in Figure S 2 where base case analysis is repeated with weights of 0.5 for each mechanism; no significant differences are observed however. In the special case where weights are put to zero, no external signal would inform service quality and capability goals and the dynamics change notably, becoming path dependent and anchored to the initial capability and quality levels.

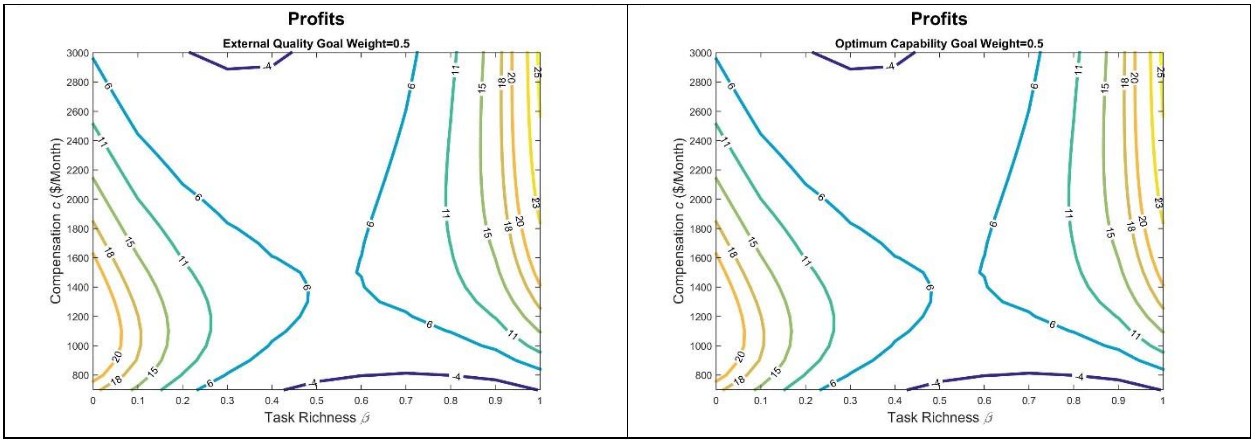
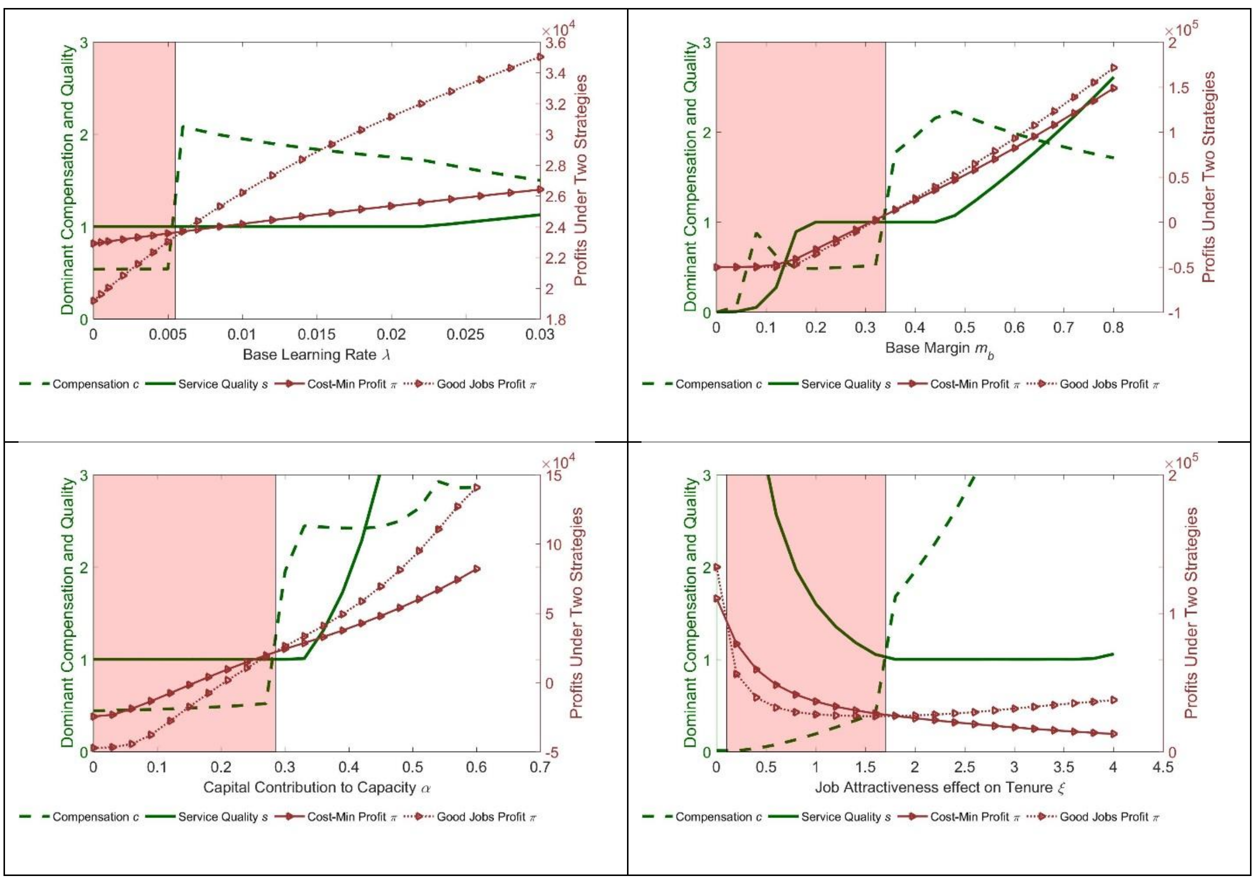


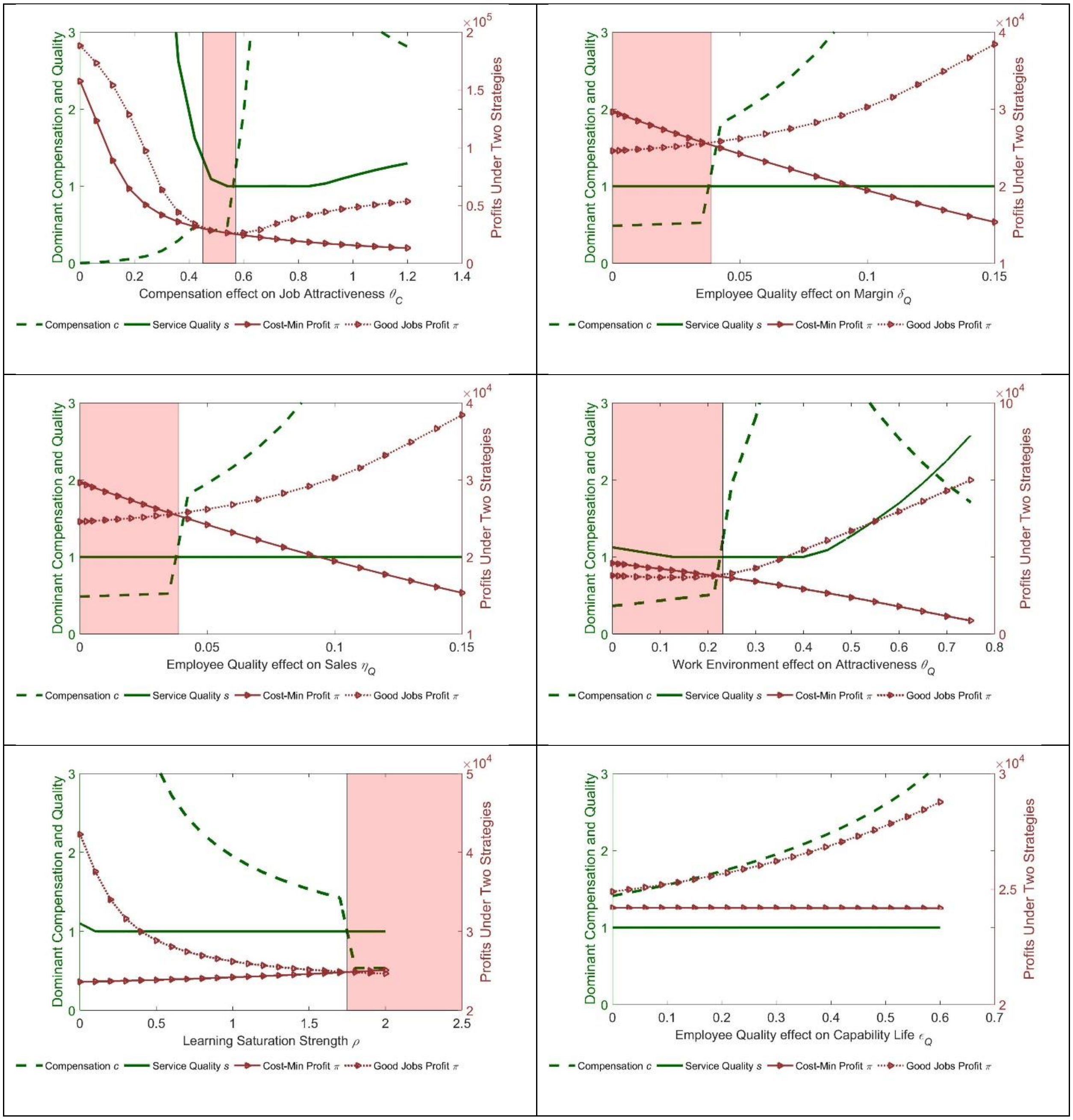
Figure S 2- Sensitivity of results to alternative goal setting mechanisms

A 3-Complete sensitivity analysis results

One dimensional sensitivity analysis

Figure S 3 reports the full sensitivity analysis results for all the parameters discussed in the paper and summarized in **Error! Reference source not found.**. The discussion in sensitivity analysis section provides explanations for the observed patterns in this figure.





Dominant Compensation and Quality
Profits Under Two Strategies
×10^5
Compensation effect on Job Attractiveness θ_C
×10^4
Employee Quality effect on Margin δ_Q
Employee Quality effect on Sales η_Q
Work Environment effect on Attractiveness θ_Q
Learning Saturation Strength ρ
Employee Quality effect on Capability Life ϵ_Q
Compensation c
Service Quality s
Cost-Min Profit π
Good Jobs Profit π

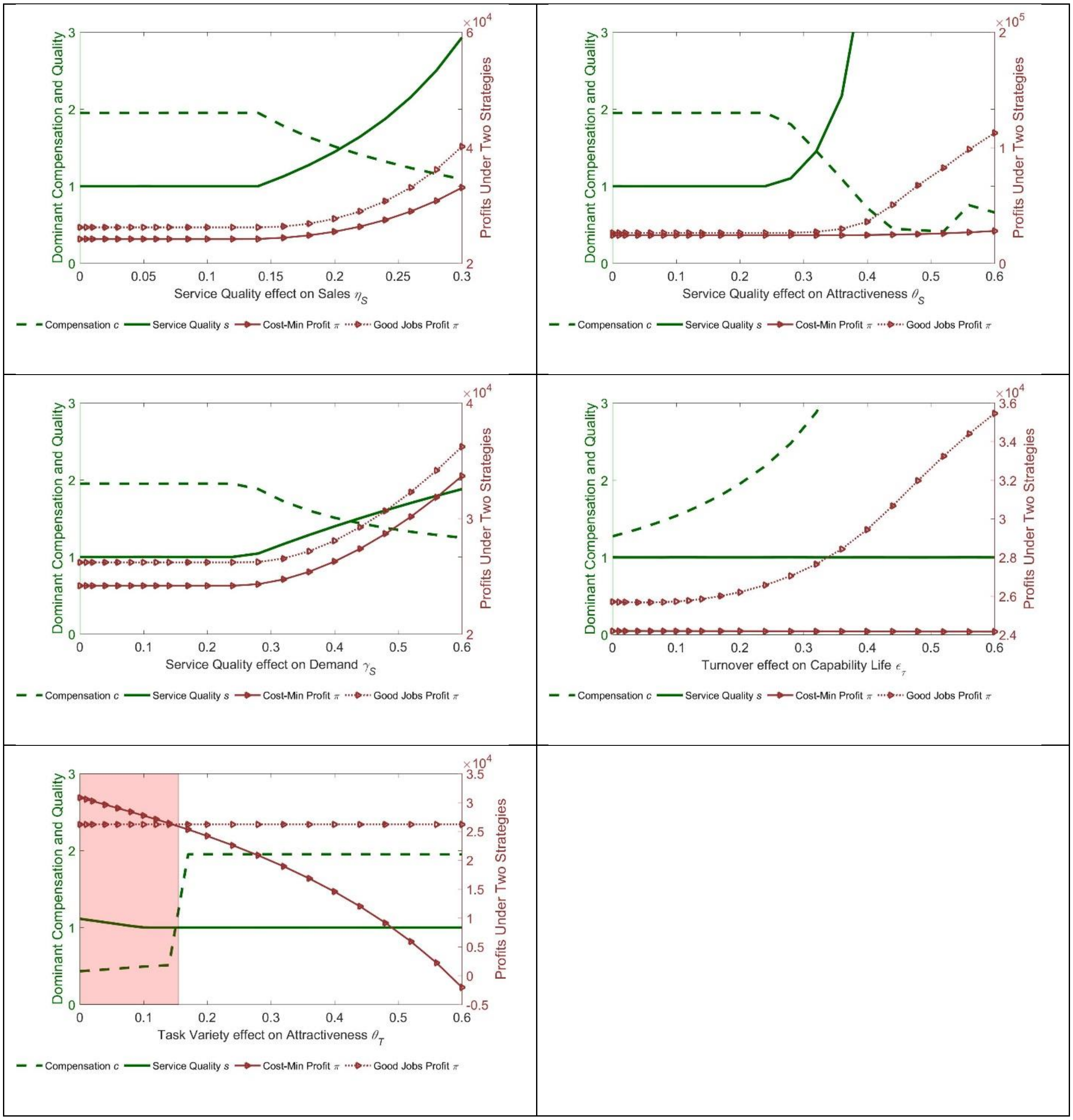


Figure S 3-Full sensitivity analysis of dominant strategy at different parameter values

Full factorial sensitivity analysis

For this analysis we change the values of 5 key model parameters at the three low-medium-high values below (Table S 1), using a full-factorial design (a total of 3^5 scenarios). In each scenario the full strategy space is mapped using values of task richness between 0 and 1, and compensation between \$500 and \$4500 per month. For each scenario the number of peaks, and their locations on the four possible quadrants (determined based on Compensation and Task Richness thresholds of \$2000/Month and 0.5 respectively) are recorded. We label these quadrants as HH (for High Compensation and High Task Richness), HL, LH, and LL. We then record which peak dominates the results, so a scenario that is coded with a dominant peak of LH, has had the profit maximizing peak at low compensation and high task richness. In a few cases more than one peak is found on a single quadrant; to simplify the analysis we only call a scenario multiple-peaked if there are peaks in at least two quadrants.

	Parameter (lables)	***Low***	***Medium***	***High***
α	Capital contribution to capacity	0.1	0.3	0.8
δ_Q	Employee quality on margin	0	0.05	0.3
θ_c	Compensation on job attractiveness	0.1	0.6	1.5
θ_Q	Work environment on job attractiveness	0	0.25	0.6
ξ	Job attractiveness on tenure	0.2	2	4

Table S 1-Full factorial sensitivity analysis parameters

In 60% (145 of 243) of scenarios the HH (high-compensation high-task-richness) peak dominates. LH dominates in 28% of cases, and LL in 12%. Overall, 173 out of the 243 scenarios included multiple peaks, which we coded as another binary variable. Table S 2 also reports the number of scenarios in which at least a peak existed in each quadrant.

	HH	**HL**	**LH**	**LL**
# SCENARIOS WITH AT LEAST A PEAK	159	78	91	121
# OF SCENARIOS WITH DOMINANT PEAK	145	1	67	30

Table S 2-Number of different types of peaks and their dominance in full factorial sensitivity analysis.

Two questions drive our analysis in this section: 1) Which peak dominates? 2) When would we have more than one peak in the strategy space? We used logistic regressions to inform these questions and summarized the findings in the main body of the paper. Here we describe the details of the analysis. A full factorial analysis offers many viable combination of explanatory variables to include in a regression, and calls for a systematic exploration of this space. We applied both mechanistic methods (e.g. stepwise regressions) and more theoretically driven arguments (e.g. based on our understanding of the model's main mechanisms) to explore the independent variables that we could include in the regressions and iterated between this exploration and improving our understanding of the model mechanisms. We found the theoretically driven search to be more effective in focusing on a small subset of variables that explain a large portion of variation in the results. The final regressions shown in Table S 3 are selected based on this simplicity criterion.

	HH	*LH*	*LL*	*Multiple Peaks*
Intercept	-2.26 (0.34)	-1.89	-129.85	1.08 (0.62)
ϑ_C		40.07	306.97	7.61 (1.6)
α				1.14 (1.01)
ϑ_Q				-2.75 (0.86)
δ_Q				-12.48 (1.87)
ϑ_C^2		-71.75	-147.18	

$\alpha\delta_Q$			-72.6 (21.79)	
$\vartheta_Q\xi$			-3.87 (1.16)	
$\alpha\vartheta_Q$	5.94 (1.67)			
$\alpha\vartheta_C$	4.8 (1.56)			-8.22 (2.1)
$\delta_Q\vartheta_C$	10.62 (2.96)			
$\alpha\vartheta_C\xi$	2.68 (0.9)			
AUC	**0.96**	**0.95**	**0.95**	**0.92**

Table S 3-Logistic regression results for predictors of dominant peak and existence of multiple peaks. All models and parameters are statistically significant; AUC reports area under the Receive Operating Characteristic (ROC) curve and is a measure of goodness of fit for the model (changing between 0.5 and 1). Due to limited variation in explanatory variables (only changing at 3 values), multiple (infinite) solutions exist for some parameters, in which case one is reported and standard deviations are excluded.

A 4-Analytical equilibrium for simplified model

Equilibrium performance for a simplified version of the model can be found analytically. To this end we can remove learning and training from the model which simplifies the equilibrium conditions significantly. Next, we use the following arguments to specify the equilibrium values for the state variables of the model:

- Baseline quality can be found using the equation for new employee quality because training and learning do not change quality in the simplified model:

$$Q_N = \left(\frac{c}{c_N}\right)^{\theta_c} Q^{\theta_Q} s^{\theta_S} \beta^{\theta_T} \Rightarrow Q_{Eq} = \left(\left(\frac{c}{c_N}\right)^{\theta_c} s^{\theta_S} \beta^{\theta_T}\right)^{\frac{1}{1-\theta_Q}}$$

- Underlying Demand can be found based on its base value and the impact of service quality on demand, keeping in mind that in equilibrium service quality equals desired service quality:

$$D_{U-Eq} = d_B s^{\gamma_Q}$$

- Equilibrium capability, employees, and assets should be set to their desired levels, C_D, E_D, and A_D, discussed above. These are:

$$A_{D-Eq} = B_{D-Eq}\alpha(1-\beta)/C_A$$

$$C_{D-Eq} = B_{D-Eq}\alpha\beta/C_C$$

$$E_{D-Eq} = \frac{B_{D-Eq}(1-\alpha)}{C_E} + \frac{C_{D-Eq}}{e_C Q_{Eq}}$$

Where desired budget in equilibrium, B_{D-Eq} is:

$$B_{D-Eq} = \frac{sD_{U-Eq}}{\kappa\left(\frac{\alpha\beta}{C_C}\right)^{\alpha\beta}\left(\frac{\alpha(1-\beta)}{C_A}\right)^{\alpha(1-\beta)}\left(\frac{1-\alpha}{C_E}\right)^{(1-\alpha)} Q_{Eq}^{(1-\alpha)\beta}}$$

We can then replace these state variables in various model equations to calculate the equilibrium profit:

$$\pi_{Eq} = D_{U-Eq} p l_b m_b Q_{Eq}^{\eta_Q \delta_Q} s^{\eta_S} - \left(c + \frac{c_h}{\tau_{V_b} Q_{Eq}^{\xi}}\right) E_{Eq} - \frac{c_N}{e_C t_b a_A} A_{Eq} - C_{Fixed}$$

In short, both equilibrium conditions and the profits in equilibrium could be calculated analytically after the simplifications discussed above. However, the resulting expression for profit (as a function of model parameters) is quite complex and the optimization problem to maximize profits as a function of compensation, desired service quality, and task richness cannot be solved analytically; thus even in the simplified model a numerical approach is required for calculating optimal strategy.